Market Performance under Different Penalty Design: Experimental Evidence on an Emissions Trading Scheme with Auctioned Permits

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Abstract

Penalty design is essential to ensure that the effectiveness and efficiency goals of an emissions trading scheme are achieved. We focus on penalty types and penalty levels to assess how penalty design might affect compliance strategies and market performance. Laboratory experiment using student subjects was run in order to control for market parameters under which the emissions trading scheme operates. We find that penalty design does not yield any differences in auction price. However, contrary to the theory which predicts that compliance rates will not vary with regard to penalty level as long as it is set above the permit price, our results show penalty level induces higher compliance rates within the Fixed Penalty Rate treatment, but not within the Make-Good Provision treatment. With regard to penalty type, we find that the Make-Good Provision which can be viewed as a 'quantity penalty' provides a stronger investment and compliance incentive. Furthermore, our finding reveals a trade-off between efficiency and compliance in the trading scheme as penalty design which encourages higher compliance rates corresponds to lower efficiency levels. It is plausible that penalty design indirectly affects auction price under the presence of risk aversion.

JEL: Q58, C91, L51, K42
Keywords: emissions trading scheme, penalty design, auction, compliance, market performance, experiment

1. Introduction

Penalty design that ensures the compliance of market participants is one of the key market design elements which enables an emissions trading scheme to deliver its environmental effectiveness and economic efficiency. When a firm has not surrendered the number of permits required for the greenhouse gases it has reported, it will need to pay the penalty and/or has to 'make-good' for the missing permits. From an economic perspective it is often interesting to see how firms choose to comply in a particular setting in order to maximise their profits.

Generally three types of penalty are widely used in existing emissions trading schemes. The first is the fixed penalty rate (FPR) which defines a constant fine for each permit missing, for example the New South Wales Greenhouse gas Abatement Scheme and the Los Angeles Regional Clean Air Incentives Market (LA Reclaim) for NOx and SOx pollutants. The second penalty type is the Make-Good Provision (MGP) which requires firms to make up for their permit shortfall with a particular ratio in the following period. In this case firms do not have a direct financial penalty to pay, for instance the US Ozone Transport Commission NOx Budget trading program imposes a 3:1 ratio of make-good provision. The last penalty type is a mix of fixed penalty rate and make-good provision (mixed penalty). This is the most widely used penalty design which serves as a double penalty to ensure that the environmental goal of the scheme is maintained. This approach has been used in the EU ETS and some US emissions trading schemes. These practices are intended to prevent the continuous carrying over of the permit shortfall which in the end might undermine the scheme's reduction target in a long term.

An important question with regard to penalty design is its effectiveness. Basically a penalty is designed such that firms will choose to comply because the cost of being compliant is cheaper than the cost of being non-compliant (having a permit shortage). Thus a firm will prefer to buy enough permits to cover its emissions than to have a permit shortage which imposes penalty. Unfortunately, the equilibrium permit price, as a benchmark to a penalty level, is normally not known to either the regulator or the firms. As the distance between the permit price and the penalty level is decreasing, the marginal benefit of being non-compliant is increasing. Thus there is an important question of at what level should the regulator sets out the penalty in the beginning when they do not have perfect information to reveal the equilibrium permit price.

Looking at the compliance level as the outcome of a penalty design, the existing schemes show that most of them have very high compliance rates. Those trading schemes have shown that permit prices can be quite volatile, thus the distance between penalty levels and permit prices vary accordingly. The Australian Carbon Pollution Reduction Scheme (CPRS) proposal has linked the penalty level to the auction price in an attempt to ensure the penalty level tracks slightly above the expected permit price so that the distance is maintained.

Numerous theoretical work on enforcement in the context of pollution control has existed. Among others, Malik (1990) examines compliance of an emissions trading scheme and employs a stylised model in which the enforcement model focuses on the parameters of audit probability and magnitude of penalty. By allowing for noncompliance rather than seeking for an optimal enforcement scheme, his model shows that the presence of noncompliance will alter the equilibrium permit price and the resulting market efficiency. Nevertheless, there are only a few studies which discuss penalty types with regard to emissions trading schemes. Nentjes and Klaasen (2004) discuss the compliance incentives under the Kyoto Protocol. Nevertheless, they look at emissions trading scheme as an implicit compliance incentive in the Kyoto Protocol rather than focusing on the penalty design within the trading scheme itself. It is argued that in cases where sellers' reputation cost is lower than that of buyers' and sellers liability applies[1], the provision to trade will induce overselling on the seller's part which results in lower compliance rate. Nevertheless, it is necessary to point out that this conclusion is only valid where no further penalty is enforced for sellers' non-compliance. Furthermore, this condition also does not exist in the existing trading schemes as penalty costs will be the same for all firms and reputational costs will be additional penalty costs on top of the trading scheme's penalty system. A study by CPB (2003) discusses restoration rate or make-good ratio as a means to induce early action rather than making a delay in investment. A general equilibrium model is used to analyse the appropriate restoration rate under some scenarios of restoration rates and the degree of delay among 6 blocks of countries. It is concluded that the interpretation of the results are highly dependent on the particular setting of the model.

[1] Seller's liability rule states that a sanction is imposed on permit sellers who have oversold their permits without making sufficient emissions reductions.

Considering that each trading scheme can have very different design elements and operate in different industries or market structures which are not directly comparable one to the other, assessing the effectiveness of a particular penalty design empirically using field data is very difficult. Experimental economics offers an approach in which subjects' decision-making can be observed, while the parameters and environment in which a market operates are controlled within the laboratory. To our knowledge, there is a limited number of experimental study which focuses on enforcement in the context of emissions trading scheme. Cason and Gangadharan (2006) use dynamic enforcement model to assess the interaction among banking, uncertainty regarding emissions, and compliance with regulations. Subjects are required to self-report their emissions level. The penalty design applies higher different audit probability and fine when a subject is found to make false report on their emissions level. Their results show that banking provision induces more non-compliance. Murphy and Stranlund's study (2007) investigates the effects of targeted enforcement by applying differing marginal penalty, in terms of audit probability and penalty level, to different characteristics of firms. They confirm Stranlund and Dhanda (1999) theoretical model that targeted enforcement does not increase the effectiveness of the enforcement scheme, although firms who are expected to be net buyers show higher level of noncompliance than those who are expected to be net sellers.

The existing literature seems to focus more on different audit probability and marginal penalty, targeted enforcement, and cheating as the main enforcement elements in an emissions trading scheme. Taking a rather different perspective on enforcement model, our study focuses on the types and level of penalty under the presence of perfect monitoring, hence we abstract from the effect of audit probability. We believe that even in the case when we have perfect enforcement as well as costless sanctioning, it is interesting to see firm's behaviour with regard to different penalty regimes. Since emissions trading schemes are newly created markets, penalty level gives the information of the maximum compliance costs which will facilitate price discovery in the markets. From this perspective, penalty level can also be seen as a price cap. In this sense, the level of penalty might influence price discovery process in the market. Even further, the penalty type itself might imply different effects on firm's behaviour.

The make-good provision can be seen as a quantity penalty where the non-compliant firms are allowed to 'borrow' from future permits, with its relevant cost dependent upon the future permit price. Thus the greater uncertainty about future permit price will put more pressure on that cost of borrowing and there is also uncertainty regarding marginal penalty rate. On the other hand the fixed penalty rate implies a fixed per unit cost of violation (fixed marginal penalty rate).

Our focus is on the effects of penalty design on market performance of an emissions trading market. We examine efficiency, permit prices, standard deviation of prices, compliance strategy, and compliance level as some measures of market performance. In particular, we would like to investigate how a particular type and level of penalty will impact on firm's compliance level and compliance strategy: investment decision and permit holding. As the

Australian proposed model employs a mixed penalty design in which the penalty is set very close to the auction price and the make-good factor is one, it is possible that the design will induce strategic bidding in an effort to drive down firms' compliance costs. Thus we also include this penalty design in our experiment.

2. Experimental Design

We have 5 treatments with the level and the type of penalty as our treatment variables. For each penalty type, the Fixed Penalty Rate (FPR) and the Make-good Provision (MGP), a treatment of low and high level of penalty is conducted. Additionally we also have a Mixed Penalty which combines both FPR and MGP. In this Mixed Penalty a low ratio of MGP is applied and the penalty rate is linked to last auction price, similar to the Australian model.

Table 1 Treatment Cells

Penalty Design	Penalty level	
	Low	High Level
Fixed penalty rate (FPR)	1.2 x equilibrium permit price (Treatment I)	3 x equilibrium permit price (Treatment II)
Make-good provision (MGP)	1:1 ratio (Treatment III)	3:1 ratio (Treatment IV)
Mixed Penalty	MGP low level + fixed penalty rate (1.2*auction price) Treatment V	

The experiment consists of 3 sessions in which 2 groups of 8 subjects participate in each session and the group remains the same for the whole session. Thus we have six observation groups for each treatment. In each session, subjects participate in Holt and Laury (2002) lottery choice game before taking part in the emissions trading game[2]. However the payoff from Holt and Laury experiment is only determined after the emissions trading game is concluded in order to avoid having any endowment effects from that lottery choice game.

Subjects are undergraduate and postgraduate students at the University of New South Wales who are recruited through ORSEE online recruitment system (Greiner 2002). Each subject can only participate in one session resulting in a total of 240 students participated in the experiment. Each session lasts for about 2 hours and subjects earn an average of $24.48 for the emissions trading game and $34.20 for the session.

The emissions trading game was programmed using University of Zurich's Z-Tree program (Fischbacher 1999). Eight subjects in one group play six repeated rounds and each round comprises of 2 sub periods. Although we use terms related to the emissions trading scheme

[2] Holt and Laury (2002) experiment asks subjects to choose the 10 paired lottery choices of A and B in which the probability of getting the higher payoff in both choices are increased. A consistent risk preference attitude will involve a change of choice from the safer lottery A to the lottery B somewhere along the 10 pairs. The combinations of safe and risky choices constitute an index of 1 to 9, in which higher index levels represents higher risk aversion.

context, subjects receive the instructions in a neutral terminology. Emissions or other environmental terminologies are not mentioned at all in the instructions[3].

Subjects are told that they are firms which need to have a unit of license for each unit of good X that they produce. These permits expire at the end of each sub period. If firms do not hold enough permits, than they will incur a penalty. The regulator determines emissions cap which is set at 50% of firm's initial emissions level and this cap remains the same for both sub periods throughout the experiment. Firms have two compliance strategies: 1) by making investment decision in an abatement technology, and 2) by holding enough permits to cover their emissions level. Firms are allowed to be compliant by undertaking both measures though each firm's optimal compliance strategy is choosing only either one of them.

The key features of the emissions trading game are as follows:

1. Stages of the game

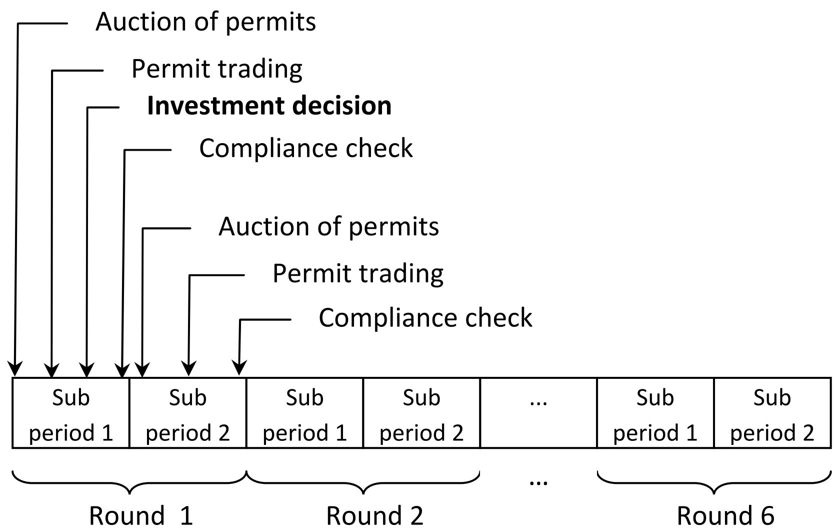

Figure 1. Stages in the Emissions Trading Game

There are four stages in the emissions trading game as shown in Figure 1.

a) Stage 1: Auction of permits

Initial allocation of permits to firm is carried out through auction. In this first stage, each firm needs to submit their non negative bidding quantity at the auction bidding rounds. The auction is conducted using ascending clock auction[4]. In case the aggregate demand is greater than the supply, then the auction price is the next-to-last bidding price and firms will obtain the quantity at their last bidding round plus any remaining excess supply. The excess supply is allocated according to the order of the fastest bidders. While bidding

[3] The instructions are available upon request.

[4] In an ascending clock auction, the price is the clock and bidding price is raised as long as the aggregate bidding quantity (aggregate demand) is higher than the total supply.

round continues, firms are given the information about the gap between aggregated demand and the supply. This auction price thus serves as an early price signal for firms.

The bidding price starts at the price of EX$18 and the price is raised in EX$ 5 increment. We start with a bidding price lower than the lowest firm's Marginal Abatement Cost to allow all firms to submit a positive bidding quantity. We choose those price parameters in order to have enough bidding rounds that will reveal more price discovery process but at the same time keeping the time for the auction stage not too long so that the experiment does not take too much time.

b) Stage 2: Permit trading

After receiving their permit allocation at the auction, firms trade permits using posted-offer continuous-double auction mechanism for 1 minute[5]. This mechanism allows a firm to be either a buyer and/or a seller. Firm is free to accept any submitted (buy or sell) public offers at anytime during the trading stage although improved bidding rules are applied to encourage faster convergence of offer prices[6]. Trade can only take place for each unit of license at a time. This double auction mechanism is a widely used trading institution for economic experiments and it has proven to results in high efficiency. Following each trade, firms receive updated public information regarding standing offers and trading prices, as well as private information of their money and permit holding. At the end of the trading stage, the average trading price of that sub period is revealed to firms as a point estimate of the price signal.

c) Stage 3: Investment decision (only for sub period 1)

The investment decision can be seen as a way to activate firm's abatement technology hence the investment cost is represented as marginal abatement cost rather than a lump sum capital cost. Investment decision in abatement technology will ensure firm's compliance for both sub periods of a round. In order to reflect the irreversibility of investments, firms can only make investment decisions in the first sub period and they cannot be changed in the second sub period. At this stage, firms also find out whether they have a short or long position before they make investment decision. Partial investments are not allowed in order to encourage firms to learn about their best compliance strategy based. If firms are short of only a few permits and decide to invest, they will be over-compliant as investment automatically guarantees firm's compliance and firms can no longer sell their permits.

[5] We allow a relatively short trading period for the spot markets as we believe the main permit allocation should take place at the auction. Consequently, permit trading serves as a secondary trading institution to 'clean-up' in case auction does not result in the expected allocative efficiency.

[6] Improved bidding rules require that the buy offer should be higher than the current highest standing buy offer while the sell offer should be less than the lowest standing sell offer.

d) Stage 4: Compliance check

Compliance check is the last stage in each sub period where subjects learn about their earnings of that sub period, their compliance status, as well as the penalty imposed on them if they are non-compliant.

2. Players' characteristics:

All firms produce a homogenous product and have the same production level of 20 units in each sub period throughout the experiment. Firms are only differentiated by their constant marginal abatement cost (MAC) which is taken out of these values, $c_i \in EX\$ \{20, 25, 30, 35, 40, 45, 50, 55\}$. This MAC is randomly allocated to each firm in each round and the range of MAC remains the same in all rounds. Based on the magnitude of firm's marginal abatement costs, we have two types of firms: the low-cost firm with MAC of EX$ 20-35 and the high-cost firm with MAC of EX$ 40-55.

At the beginning of each sub period, firms receive the same total revenue of EX$ 2800 from their production activity as the price of the good is exogenous and the same for everyone. Thus the marginal revenue is constant at EX$140, but firms have different marginal valuation of each unit of good.

3. Information structure

At the beginning of each sub period of a round, subjects receive common information about their initial emissions level, emissions cap, and the penalty design. This common information is known by all firms and remains the same in all rounds. Within this stage subjects also learn private information about their marginal abatement costs, money, and required number of licenses. For sub period 2, subjects are also reminded of their investment decision and their compliance status in Sub Period 1. The information structure basically enables participants to estimate optimal decisions on whether to invest in abatement technology or buying permits in the market.

4. Banking and borrowing are not allowed.

As the focus of our experiment is on the sanction design, we simplify our two-period model to abstract from the effect of banking. By neither allowing for banking nor borrowing, we attempt to keep the market structure the same for both sub periods as banking might create an upward pressure to the expected permit price in the first sub period. Hence the expected permit price should remain the same across both sub periods of a round.

5. Penalty

The enforcement of penalty design in the emissions trading game is conducted as the following:

a) In FPR treatment, the penalty is imposed at the end of each sub period at the compliance check. In case of non-compliance, the penalty costs are deducted from firm's earnings.

b) In MGP treatments, the penalty is enforced differently between the 2 sub periods.

- Non-compliance is sub period 1 has no financial penalty but the violating firms need to surrender the quantity of the missing permits by a ratio. For example in the high level MGP treatment with a ratio of 3:1, if a firm has a shortfall of 2 permits then it has to hold additional 6 permits in sub period 2.
- As firms cannot further make-good for noncompliance at the end of sub period 2, we attempt to deter non-compliance by imposing an enormous financial penalty which is equivalent to the firm's total revenue (EX$ 2800).

6. Payoff

Firms can maximise their payoff by minimising their compliance costs or by maximising their profit from selling permits during trading stage. The payoff function is the same for all firms.

Payoff =
+ Total Revenue
+ cash balance of Sub Period 1 of the same round
– number of licenses bought in auction * auction price
– investment costs
– trading price of licenses bought during trading stage
+ trading price of licenses sold during trading stage
– penalty costs

The payoff is accumulated for all rounds and subjects' earnings are shown at the end of each round. Nevertheless, the amount of money that subjects receive in the beginning of each round (Sub Period 1) is always equal to the Total Revenue in order to avoid having any wealth effects on the subjects as the round goes on.

3. Hypotheses

In the competitive equilibrium, the permit price should lie between EX$ 35-40 in the presence of perfect compliance. Considering the design of the auction bidding price, auction price should reach its equilibrium at a price of EX$ 38. At this equilibrium, the best compliance strategy for the low cost firms is making an investment decision, while the high cost firms should be compliant by buying permits. This equilibrium permit price is achieved when each firm chooses their best compliance strategy.

Based on a simple theoretical model (Restiani 2010) and the parameter in the experimental design, we derive the following hypotheses:

Hypothesis 1: Auction price should remain the same in all treatments as the supply and demand structure remains the same.

Hypothesis 2: In the Fixed Penalty Rate treatments, investment levels and compliance rates should be the same at 100% regardless of the penalty levels as long as the penalty rate is higher than the equilibrium permit price.

Hypothesis 3: The make-good ratio should not affect investment levels and compliance rates in the Make-Good Provision treatments as long as it is set equal or higher than one, under the assumption that prices remain the same in both sub periods.

Hypothesis 4: In the high penalty level, compliance rates and investment levels in the Fixed Penalty Rate treatments should be the same with those in the Make-Good Provision treatments. As for the low penalty level, similar results are expected although the penalty level is not as comparable since the penalty rate factor is 1.2 while the make-good factor is 1.

Hypothesis 5: The Mixed Penalty design should yield the same compliance rates as in the Fixed Penalty Rate and Make-Good Provision treatments.

4. Results

4.1. Descriptive Statistics

4.1.1. Subject Risk Preferences

The Holt & Laury (2002) lottery choice experiment shows that more than 75% of the subjects risk preferences are risk neutral, slightly risk averse, or risk averse, as expected. We observe that some subjects made inconsistent risk preference choices by changing from one lottery to another one more than once. However, these inconsistent choices only involve roughly about 20% or less of the subjects in each treatment (Figure 2). The data of subjects' risk preferences are later used in the estimation models as risk attitude might be an important determinant of compliance strategy and auction price.

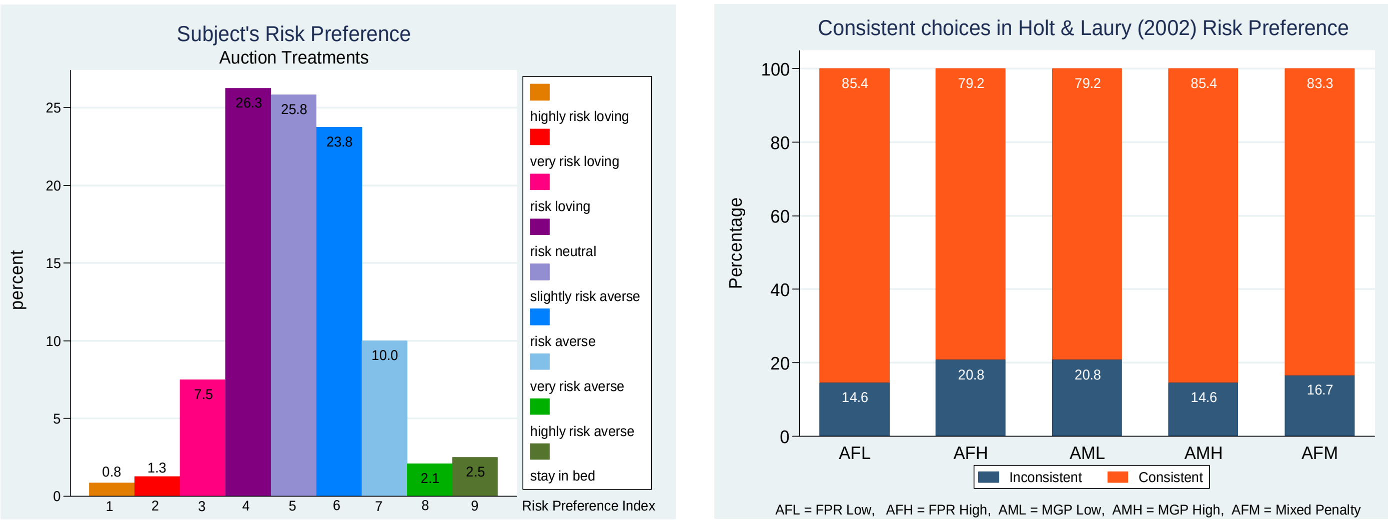

Figure 2. Results from Holt and Laury (2002) experiment

4.1.2. Discussion on Descriptive Statistics

The statistics summary of some variables of market performance is presented in Table 2. Although differences in the mean values of those variables are observed, further tests are needed to confirm that those differences are statistically significant. Therefore the next section will elaborate how the hypotheses are tested using non-parametric tests of equality of distribution.

Table 2. Statistics Summary across Treatments

Treatment	Effi-ciency	Auction price	Mean Trading prices	S.d. Trading prices	Trading vol.	Ave. Permit Price	S.d. Ave. permit price	Invest-ment Level[a]	Com-pliance Rate[a]
FPR Low (AFL)	0.890	45.01	33.63	5.36	11.75	43.66	10.04	1.130	0.810
FPR High (AFH)	0.862	48.21	36.25	6.70	10.25	46.80	10.69	1.215	0.913
MGP Low (AML)	0.855	42.58	35.91	15.82	6.35	41.94	15.92	1.292	0.927
MGP High (AMH)	0.836	48.28	38.85	5.63	8.22	47.77	22.72	1.174	0.917
Mixed Penalty (AFM)	0.836	45.57	40.85	5.23	6.81	45.30	11.51	1.319	0.941
Optimum	1.000	35-40	35-40	0		35-40	0	1.000	1.000

Discussion on Price Variables

The results show that higher penalty level in each penalty type induces higher auction price (Figure 3). It is also clear that auction has served at the primary market for distributing permits instead of the spot market (trading stage) with trade volume being less than 15% of total number of permits in the market. Furthermore, the mean of trading price is always lower compared to the auction price in all treatments.

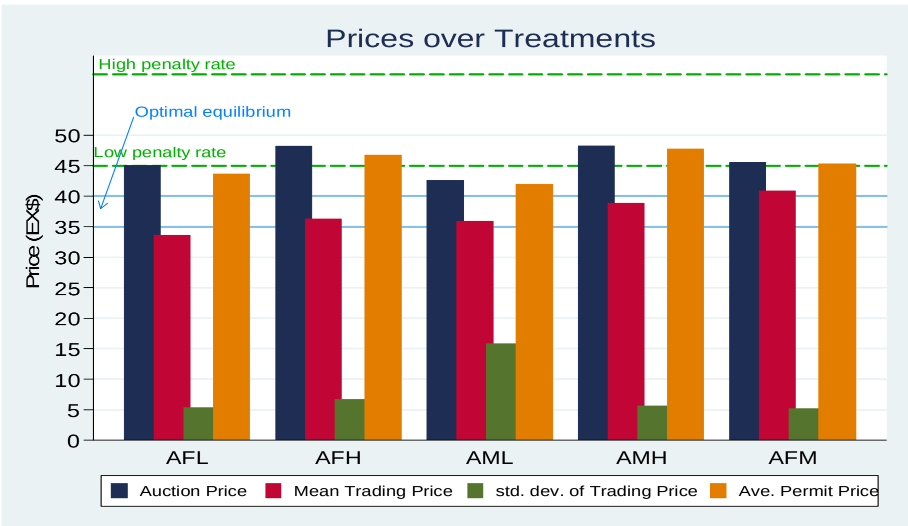

Figure 3. Prices variables over treatments

In line with the auction price, treatments with higher penalty level also reveal higher mean of trading prices. The mixed penalty rate, which can be viewed as the double penalty regime, results in the highest mean of trading prices. However, the effect of penalty level is rather ambiguous with regard to standard deviation of trading prices as opposing trend is observed in FPR and MGP treatments. The smallest magnitude of this parameter is shown by the mixed penalty treatment.

The difference between auction price and the mean of trading price might indicate that the spot market is used to clean any unwanted excess allocation of permits that a subject obtain, thus the resale value of the permit is lower as subjects are keen to minimize the loss from getting those excess permits at the auction. On the other hand, it can also highlight how high the permit demand is at the auction, which might be due to strategic bidding behaviour rather than the real subject's need of getting permits for compliance. The data shows that in 120 out of 360 observations, the auction price is equal or higher than the mean of trading prices, which confirms that some subjects realise gain from trading in the spot markets.

The average permit price reflects the volume-weighted average calculated from the auction and trading price, hence it is not much different to auction price. Compared to the range of prices in the optimal equilibrium, the average permit price is constantly higher than the optimal range in all treatments, but the prices are hovering around the low level of FPR and still well below the high level of FPR. The same pattern of the effect of penalty design on the standard deviation of the average permit price is similar as that of the auction price.

Discussion on Investment Level, Compliance Rate, and Compliance Strategy

With regard to the main effects of penalty design on environmental effectiveness, we examine these effects through the variables investment level and compliance rate. The variables are expressed in terms of the number of firms and compared to the optimal level. At the optimal level, there should be 4 investing firms and 8 compliant firms which is translated in the optimal scale of unity (Figure 4).

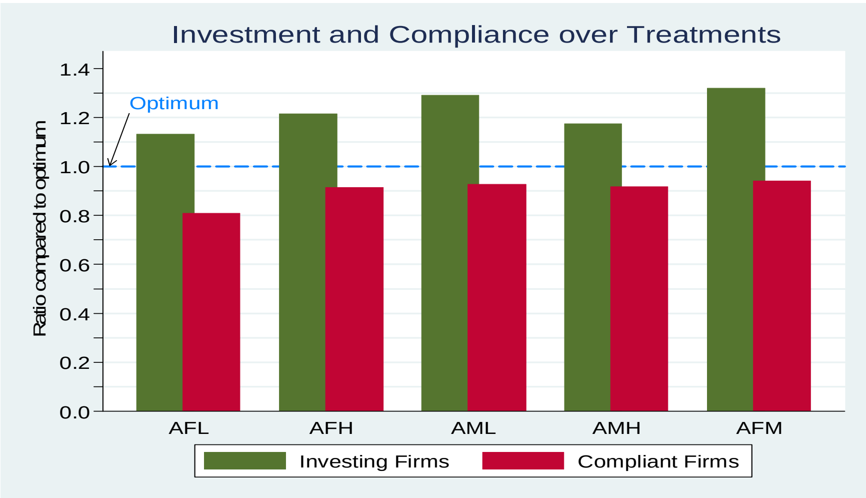

Figure 4. Investment and Compliance Level over Treatments

Similar to the trend in the standard deviation of trading prices, the investment level is also higher with higher penalty in FPR treatments, but not in MGP treatments which shows an opposite trend. A general incidence of over-investment is observed in all treatments as the mean of investment level has a ratio of higher than 1 compared to the optimal level. It is seemingly plausible that higher penalty level leads to higher investment level as the mixed penalty design, which imposes double penalties, exhibits the highest investment level. Nevertheless this inference is only valid after a regression model is performed to control for all influencing factors.

Interestingly, the observed over-investment is not translated into full compliance level (100% of firms are compliant), although the same trend in investment level is also shown in the number of compliant firms. Likewise, higher penalty level induces higher number of compliant firms in FPR treatments and the mixed penalty displays the highest compliance level. This means that some investing firms still hold excess permits at the end of a sub period and render the buyers in short position. A plausible explanation for that is firm's prevalent behaviour in an attempt to realise gain from arbitrage trading. The competitive nature of clock auction can push the prices to a fairly high level which makes it more difficult for firms to make profit in the spot market within the limited trading time.

Comparing how firms choose their best compliance strategy in FPR and MGP treatments, we have a conjecture that the quantity penalty nature of MGP treatments bring about much more prices uncertainty for firms and more deterrent effects which resulted in more volatility in the market. This volatility over time makes it more difficult for firms to arrive at their best compliance strategy as price signals are more scattered.

In the theoretical optimal equilibrium, firms with low marginal abatement costs (low MAC firms) should choose investment decision as their sole compliance strategy, while those with high marginal abatement costs (high MAC firms) should not invest and just buy permits as their best compliance strategy. However, when the auction price turns out to be higher than the optimal equilibrium, firm's decision about its best compliance strategy will not be as easy as expected, especially for those high MAC firms.

The data confirms that across treatments firms with low MAC have higher compliance rate than high MAC firms (Figure 5). Hence, buying permits are not always perceived as the best compliance strategy for high MAC firms as prices fluctuate at level higher than the theoretical equilibrium permit price. Although the low MAC firms do not always choose investment as their best compliance strategy, the compliance rate of these firms is still higher than the high MAC firms. The test statistics verifies that the differences in compliance rate and investment decision over firm type are highly significant ($p<0.001$). For both firm types, the mixed penalty design (AFM) gives the clearest compliance incentive unlike the FPR low level. In terms of penalty type, MGP treatments also provide better compliance incentive than FPR treatments.

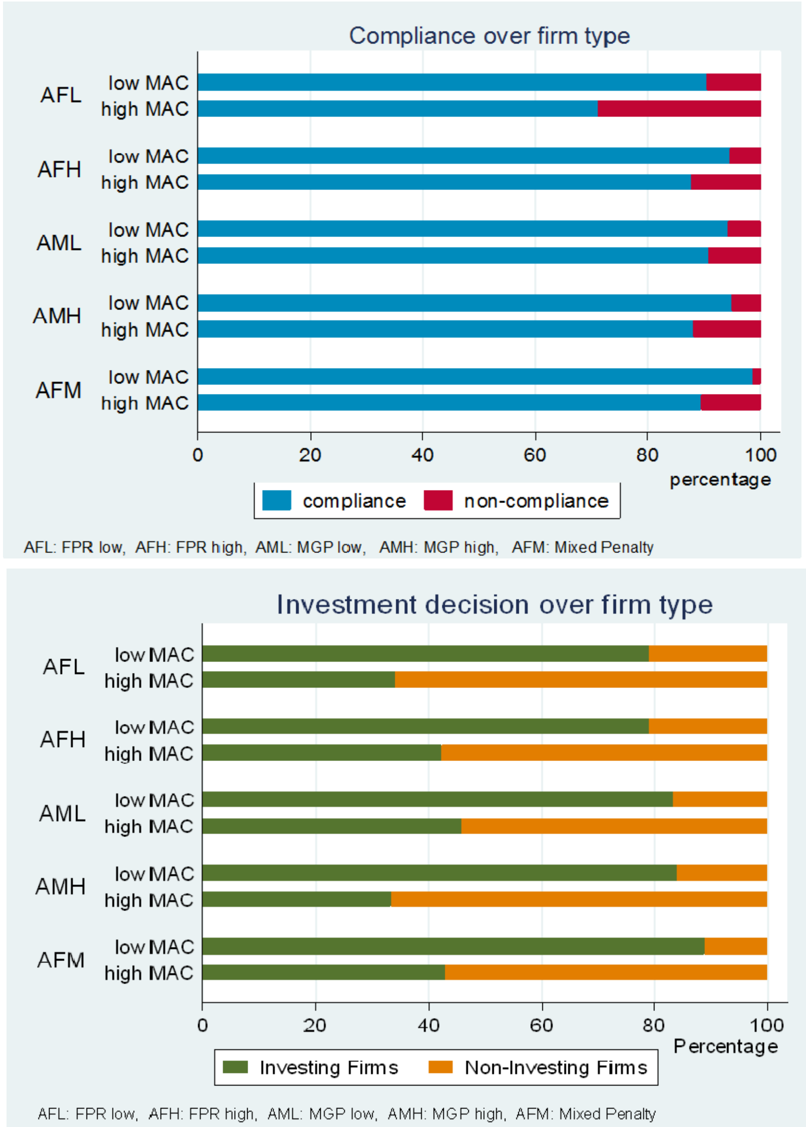

Figure 5. Compliance Rate and Investment Decision over Firm Type

Discussion on Efficiency

At the end of each sub period, efficiency is a variable which sums up the measure of market performance under the presence of non-compliance. As permit prices rise, firms will need to spend additional costs of buying permits, hence the efficiency in the market will be compromised. The data shows that lower penalty level results in higher efficiency and the FPR treatments perform better than MGP and Mixed Penalty treatments in this regard (Figure 6).

4.2 Hypotheses Test of Treatment Effects

4.2.1. Auction Price

Result 1: There are no differences in auction prices across all treatments (consistent with Hypothesis 1). Furthermore, auction prices remain above the optimal equilibrium level.

Support: Kruskal-Wallis non-parametric test is employed to test whether all 5 treatments have the same distribution in terms of auction price. Each observation group is assumed to be independent and no further assumption is taken with regard to the distribution of the data. The test results in a p-value of 0.1537 and thus we cannot reject the null hypothesis that the prices come from the same underlying distribution.

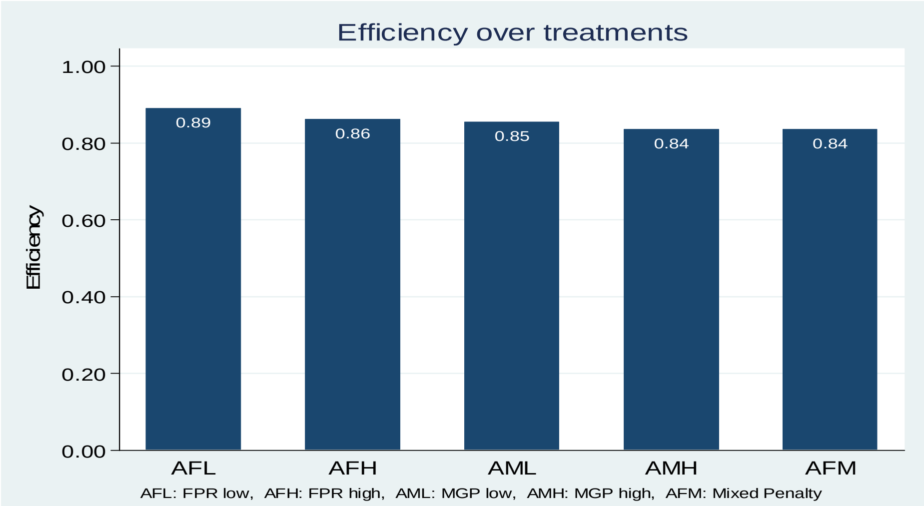

Figure 6. Efficiency over Treatments

4.2.2. The Effect of Penalty Level in Fixed Penalty Rate

Result 2: There are differences in compliance rates but not in the investment level between low and high level penalty treatments of the Fixed Penalty Rate. The compliance rate is statistically higher in the high level penalty treatments (inconsistent with Hypothesis 2).

Support: As a test of the treatment effect is required only for 2 groups of independent samples, the Kolmogorov-Smirnov test is conducted to assess if the two groups come from the same underlying distribution. The test statistics show that the investment level is not statistically different between the two penalty levels (p-value of 0.0179). On the other hand, the test statistics is highly significant for compliance rate (p-value of 0.0000).

4.2.3. The Effect of Penalty Level in Make-Good Provision

Result 3: Penalty level does no affect investment level and compliance rates in the Make-Good Provision treatments (consistent with Hypothesis 3).

Support: The Kolmogorov-Smirnov test statistics yields a p-value of 0.419 for investment level and 1.000 for compliance rates. The coefficient confirms that the estimates are derived from the same population distribution.

4.2.4. The Effect of Penalty Type

Result 4: In the high penalty level, there are no significant differences in terms of investment level and compliance rates between the Fixed Penalty Rate and the Make-Good Provision (consistent with Hypothesis 4). On the other hand, different compliance rates are observed in *the low penalty level in which the Make-Good Provision treatments have higher compliance rates than the Fixed Penalty Rate treatments. This difference is not found in investment levels (inconsistent with Hypothesis 4).*

Support: For the high penalty treatments, the test statistics show we cannot reject the null hypothesis that the two samples are derived from the same population distribution (p-value = 1.00) for both investment level and compliance rate). With regard to the low penalty level, we obtain a highly significant statistics for compliance rate (p-value =0.000) but not for the investment level (p-value =0.213)

4.2.5. The Effect of Mixed Penalty

Result 5: The Mixed Penalty design provides the same investment and compliance incentives as with the Make-Good Provision treatments, however the same conclusion cannot be drawn when the comparison is made to the Fixed Penalty Rate as differences are found in both investment levels and compliance rates (inconsistent with Hypothesis 5).

Support: As the Mixed Penalty comprises of two penalty types with some modification, a comparison of the effect of this penalty design must be carried out with regard to those elements. Hence we assess treatment effects by making a comparison with low level MGP treatments and low level FPR (AFL) treatments. It is important to point out, that unlike the AFL treatments, the mixed penalty employs variable penalty rate over time, as penalty rate is linked to the auction price. As shown in Table 3 the test statistics are only significant when a comparison is drawn with the AFL treatment.

Table 3. Summary of Test Statistics for Treatment effects

Variable	Pairwise Comparison					
	Penalty level in FPR treatment	**Penalty level in MGP treatment**	**Penalty type for low level treatment**	**Penalty type for high level treatment**	**Mixed Penalty vs Low MGP**	**Mixed Penalty vs AFL**
Auction Price KS[a] p-value	AFL < AFH 0.419	AML > AMH 0.213	AFL > AML 0.014 **	AFH ≈ AMH 0.062	AFM > AML 0.062	AFM > AFL 0.992
Investment level KS p-value	AFL < AFH 0.419	AML > AMH 0.419	AFL < AML 0.213	AFH > AMH 1.000	AFM > AML 0.947	AFM > AFL 0.014 **
Compliant firms KS p-value	AFL < AFH 0.001***	AML >AMH 1.000	AFL < AML 0.000 ***	AFH ≈ AMH 1.000	AFM > AML 0.847	AFM > AFL 0.000 ***
Efficiency KS p-value	AFL > AFH 0.014**	AML > AMH 0.847	AFL > AMH 0.146	AFH > AMH 0.008 **	AFM < AML 0.213	AFM < AFL 0.039*

Note: [a] Kolmogorov-Smirnov test of equality of distribution
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 144.

5. Estimation models

The test of treatment effects, alas, cannot fully capture the relationship between our treatment variables and a particular variable of interest (dependent variable). Moreover, there might be some effect from subjects' characteristics. Thus we need to control for all those factors in order to isolate the treatment effects. In that view, regression models are formulated which examine further the effects of our treatment variables to auction price, investment decision, firm compliance through permit buying, and efficiency. Auction price is chosen as the first dependent variable because auction price is the first price signal which subjects receive before deciding on their compliance strategy through investment decision and permit buying at the spot market. Subsequently, investment decision and firm compliance status as the two available compliance strategies are also important dependent variables so that treatment effects of penalty type and penalty level can be verified. At last, efficiency is a crucial measure of market performance as a basis of the economic success of an emissions trading scheme.

5.1. Auction Price

Considering that auction is the first stage of each sub period in the emissions trading game, we can only include treatment variables and subjects' characteristics in each observation group as dependent variables. The data is collected for each sub period of each group; hence 360 observations are used to estimate each model. The regression model for auction price is estimated using panel data heteroskedasticity robust random-effect model.

Model 1 represents the basic model which contains the treatment variables of penalty design as the main regressors, which are the dummy for FPR treatment, dummy for high FPR treatment, dummy for MGP treatment, and dummy for MGP high level treatment. For the Mixed penalty design, the dummy for high FPR is set to zero (low level) although the penalty rate is actually varied. This measure is taken as the penalty rate is directly linked to the auction price, hence it is not independent to auction price and if penalty rate is included as a regressor the estimates will be biased toward higher significance. In view of the complexity of our experiment, *Round* and *Sub Period 2* are also included as regressors to examine subjects' learning curve over time.

In Model 2, risk-related variables are included. *Group risk preference index* represents the aggregated value of each subject's Holt & Laury's (2002) risk preference index for each observation group. The variable *inconsistent risk preference choice* also employs the same aggregation approach.

Model 3 incorporate additional control variables which are related to subject's gender and study. At individual level, the data *study program* is a categorical variable which indicates whether a subject is undertaking an undergraduate, master's, or doctoral program. For group level data, a mean value is taken for each group. The same approach is taken for the other demographic explanatory variables.

A different set of additional demographic variables are added in Model 4. These variables are related to age, household income, the number of household members, and own income. Since most of the students are not financially independent, we are controlling for the effect of these income variables to subject's risk preference. These demographic variables are measure in terms of the mean values of ordinal variables.

Table 3 shows that the sign of the explanatory variables are intuitive and consistent across all models. The coefficients on MGP treatment are always much smaller than those of the FPR treatment although both are not statistically different than zero. On the other hand the coefficients on high level MGP are about 2 to 4 times larger than those of the high level FPR, except in Model 3. It is important to point out that the coefficients on the penalty design are not statistically significant, except in Model 3 for high MGP treatment. Thus, the quantity penalty nature in the high level MGP evidently raises the demand for permit, *vis a vis* other penalty designs.

Table 4. Estimates Summary for Auction Price

Variables	Model 1	Model 2	Model 3	Model 4
Dummy for FPR	2.9861	4.3953	2.8073	3.4850
	(2.6218)	(3.0792)	(3.0787)	(3.5141)
Dummy for FPR high level	3.1944	2.3382	4.2525	3.3898
	(3.7962)	(3.0537)	(2.8568)	(3.5971)
Dummy for MGP	0.5556	1.1085	3.3148	3.4868
	(3.5854)	(3.4998)	(2.5991)	(3.1911)
Dummy for MGP high level	5.6944	6.7694	4.7335	5.2603
	(4.7587)	(4.2066)	(3.6255)	(3.9259)
Round	-2.4024***	-2.4024***	-2.4024***	-2.4024***
	(0.6777)	(0.6796)	(0.6845)	(0.6885)
Dummy for sub period 2	-0.3611	-0.3611	-0.3611	-0.3611
	(1.7946)	(1.7997)	(1.8127)	(1.8232)
Group risk preference index		-0.3280	-0.6487**	-0.6538**
		(0.2126)	(0.2412)	(0.2501)
Number of subject with inconsistent risk choices		2.5873*	2.2587**	2.1594*
		(1.1067)	(0.7914)	(0.9004)
Number of female subjects			-1.7486	-1.7091
			(1.0304)	(0.9962)
Mean of study program			-7.7089	-10.0297
			(5.4714)	(8.3486)
Mean of dummy for study field related to economics			-6.3044	-6.4279
			(6.7516)	(7.4228)
Mean of year in school			-6.8866*	-7.4070
			(2.7152)	(4.4188)
Mean of dummy for full-time study			-15.6643	-11.7578
			(27.9797)	(37.1170)
Mean of age				3.0269
				(7.3725)
Mean of household income				-0.2331
				(1.9035)
Mean of household members				0.5772
				(2.3867)
Mean of own income				0.2535
				(7.1051)
Constant	50.6167***	59.2014***	121.6472***	115.0062*
	(4.5917)	(10.9804)	(31.7207)	(48.2215)
Observation	360	360	360	360
Within correlation	0.0580	0.0580	0.0580	0.0580
Between correlation	0.0897	0.2752	0.4529	0.4581
Overall correlation	0.0627	0.0904	0.1169	0.1177
Chi2	15.4591	35.8100	75.1069	104.2794
Rmse (mean of squared error)	17.3382	17.3382	17.3382	17.3382
Sigma_u	5.5372	4.8132	4.6313	5.8458
Sigma_e	17.3382	17.3382	17.3382	17.3382
Rho (% due to u_i)	0.0926	0.0716	0.0666	0.1021
Theta	0.3294	0.2792	0.2660	0.3496

Note: Number in brackets represent standard error of the estimate.
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level

Variable *Round* has a negative sign indicating that the learning curve has a negative effect on auction price. It implies that at the beginning of the experiment, subjects put a very high demand on permits which might be due to a cautious behaviour toward achieving compliance. The coefficient on R*ound* is also statistically and economically significant. Unsurprisingly, auction price is slightly lower in Sub Period 2 as over-investment in Sub Period 1 effectively reduces permit demand. However, the coefficient is not statistically significant. In terms of goodness of fit of the model, the overall correlation value is relatively small and the model performs slightly better in explaining the variation between group than the variation within the same group of observation.

The inclusion of risk attitude-related variables in Model 2 points out that subjects who make inconsistent choices during the Holt & Laury's experiment might have irrational bidding behaviour which raises permit demand at the auction. The magnitude of the coefficient is also economically significant as the presence of only one irrational subject will increase the auction price by more than EX$2. *Group risk preference index* also shows the expected relationship in which higher risk aversion associates with more cautious bidding behaviour that results in lower auction price albeit it is not statistically significant. According to R^2 value, the goodness of fit is slightly increased in comparison with Model 1 and the between correlation is triple enhanced.

The estimations in Model 3 seem to explain better compared to the other models, however the constant term of the model is also doubled. We find that *group risk preference index* and *year in school* are also significant. The coefficient on the risk preference index is doubled compared to Model 2, while the effect of penalty design variables are spread more evenly although they remain insignificant. The additional of demographic variables in this model are correlated to the risk related variables, hence the significance of those risk-related variables are much improved. These demographic variables also show the intuitive signs. As expected, female subjects bid less aggressively than their male counterparts. With regard to study-related variables, students with higher study program, those who are studying full-time or in the economic-related field, and those with longer years in school are also more careful in submitting their bids. Nonetheless, these demographic variables are statistically not different to zero, except for *year in school.* The magnitude of the coefficient is very substantial and it indicates that if in average the subjects in one group are in the second year then it will drop the auction price by EX$12. Yet the largest marginal effect is generated by group risk preference index as the average index of slightly risk-averse corresponds to EX$ 26 drop of auction price. In terms of goodness of fit as measured by R^2, this model yields slightly higher overall correlation although the between correlation is almost double of that from Model 2.

The inclusion of more demographic variables in Model 4 does not improve the estimations in Model 3. The significant independent variables remain the same and statistics of the model does not change much.

The regression models show that the penalty design does not significantly affect price discovery process in the market, with respect to auction price. This result is consistent to the test statistics of treatment effect for Hypothesis 1. It is the risk-related variables which have the largest marginal effect on auction price. The learning effect is also confirmed as time variable *Round* remains statistically significant across models.

5.2. Investment Decision

After participating at the auction, subjects can trade at the spots market before deciding to make investment in abatement technology in Sub Period 1. During this investment decision stage, subject is given information about their final permit holding for that sub period and whether they are in a short or long position toward compliance. At this stage, if they are in a short position, then the only way they can be compliant is by making investment decision. Otherwise, they will be non-compliant for that sub period and suffer a penalty. In view of the decision process, the penalty design treatment variables, prices variable, firm type and firm's long position are used to regress investment decision. Unlike the estimation models for auction price, penalty rate is used rather than a dummy variable for high FPR because penalty rate is now independent to the investment decision, which is not the case for the auction price estimation. The data is collected from individual level data of Sub Period 1. We use panel data probit and logit estimation models because investment decision is a binary choice. The regressions summary is shown in Table 5.

The first four models are estimated with probit model and the results are consistent across models. Model 1 is performed with cluster robust standard error OLS estimator. Model 2 to Model 4 use robust random effect probit model with bootstrapped estimates. A logit model similar to model 4 is run in Model 5. As the nature of binary choice models, the interpretation of the estimation results in Table 5 is not straightforward in terms of the magnitude. Still the sign of the estimates give indications of the effect of the regressors to the dependant variable.

The estimates reveal that different penalty type provides different incentive to investment decision. FPR treatment has a negative effect on investment but this effect is trivial. On the other hand, MGP treatment significantly has a strong positive effect on investment. This finding is very reasonable since firms are allowed to have a lower marginal financial penalty with FPR treatment compared to the highly punitive MGP treatment. The effect of penalty rate is almost negligible although it is positive as expected. In constrast, high MGP level has negative effect on investment decision although it is not statistically significant. These results are in line with test statistics of treatment effects for Hypothesis 5. However, the regression models can better explain the effect of MGP treatment as they control for other factors which might influence investment decision.

According to the experimental design, high MAC firms should not invest and choose to comply by buying permit. This strategy is confirmed in the regression models as this variable has a negative sign and it is highly significant. The similar effect is also produced by firm's permit position. When firms learn that they have a long position of permit holding or they have more permits than they need, then they do not invest. In that view, firms have shown rational investment behaviour.

Auction price has a crucial effect on firm's investment behaviour. It seems that penalty design indirectly affect firm's decision to invest through its effect on auction price.

Conversely, trading prices has essentially no effect on investment decision. This proves that the main price signal for compliance strategy is given by auction as the primary market rather than the spots market or the secondary market.

Learning effect is not found for investment decision as indicated by the estimate on *Round*. Additional risk-related variables in Model 4 and Model 5 are also not significant. Other demographic variables such as subject's gender and age are also tested as regressors but the results show that they are not significant.

Table 5 Estimates Summary for Investment Decision

Regressor for investment decision	Model 1 Probit OLS cluster	Model 2 Probit RE bootstrap	Model 3 Probit RE bootstrap	Model 4 Probit RE bootstrap	Model 5 Logit RE bootstrap
Dummy for FPR	-0.045	-0.0746	-0.0713	-0.0515	-0.0534
	(0.2573)	(0.2573)	(0.2579)	(0.2767)	(0.5008)
Penalty rate	0.0023	0.0031	0.0032	0.003	0.0064
	(0.0026)	(0.0029)	(0.0029)	(0.0031)	(0.0056)
Dummy for MGP	0.5013*	0.5857**	0.5871**	0.5832**	1.0922**
	(0.197)	(0.2037)	(0.2033)	-0.1949	(0.3596)
Dummy for MGP high level	-0.3369	-0.3787	-0.3755	-0.3455	-0.5245
	(0.1775)	(0.2152)	(0.2137)	(0.1765)	(0.34)
High MAC firm	-0.8266***	-0.9084***	-0.9067***	-0.8914***	-1.6401***
	(0.097)	(0.1296)	(0.1316)	(0.1347)	(0.2509)
Auction price	0.0121***	0.0142***	0.0132***	0.0138***	0.0247***
	(0.0034)	(0.0032)	(0.0033)	(0.0036)	(0.0063)
Mean trading price	0.0000	-0.0002	-0.0002	0.0000	0.0000
	(0.0014)	(0.0019)	(0.0019)	(0.0019)	(0.0036)
Permit long position	-0.1191***	-0.1393***	-0.1394***	-0.1406***	-0.2623***
	(0.008)	(0.0113)	(0.0114)	(0.0102)	(0.0194)
Round			-0.0179		
			(0.0396)		
Group risk preference index				0.0065	
				(0.0467)	
Subjects with inconsistent risk choices				0.3338	
				(0.1798)	
_cons	-1.0329***	-1.2810***	-1.1820***	-1.3977***	-2.5122***
	(0.3073)	(0.2813)	(0.3538)	(0.3478)	(0.5691)
Statistics					
No. obs.	1440	1440	1440	1440	1440
No. subjects	240	240	240	240	240
lnsig2u _cons		-0.9627**	-0.9615**	-0.9972**	0.2213
		(0.2987)	(0.3008)	(0.3795)	(0.422)
Log likelihood	-448.63	-431.01	-430.859	-429.065	-422.93
'R^2'	0.5433				
Wald chi^2	303.1957	227.3476	221.2588	285.8775	229.7005
% Correctly predicted	88.75				

Note: Number in brackets represent standard error of the estimate.
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level

The statistics of the models show that the addition of more explanatory variables does not substantially increase the goodness of fit of the model. Overall, the models have a considerably high prediction power of 88.75 % as shown by the basic model (Model 1).

5.3. Compliance Decision through Permit Buying

As investment decision automatically ensure firm's compliance, this section discusses estimation models of compliance decision only though permit buying. Therefore, only observations from those subjects who do not make investment decision are used in the regression. Considering that compliance status is a binary variable, the regressions are performed with probit and logit estimators for panel data.

Table 6. Estimates Summary for Compliance Decision

Regressors for compliance decision	Model 1	Model 2	Model 3	Model 4	Model 5
	Probit OLS cluster robust	Probit RE bootstrap	Probit RE bootstrap	Probit RE bootstrap	Logit RE bootstrap
Dummy for FPR	-0.0872 (0.1653)	-0.1416 (0.1911)	-0.1397 (0.2206)	-0.142 (0.2189)	-0.2593 (0.3500)
Penalty rate	0.0087*** (0.0021)	0.0089** (0.0028)	0.0088*** (0.0024)	0.0089*** (0.0025)	0.0152*** (0.0046)
Dummy for MGP	0.9548*** (0.2019)	0.9796*** (0.2354)	0.9776*** (0.2383)	1.0025*** (0.2298)	1.6834*** (0.4696)
Dummy for MGP high level	0.0779 (0.1801)	0.1307 (0.1870)	0.1306 (0.1796)	0.1235 (0.2176)	0.1954 (0.3814)
Round	0.051 (0.0291)	0.0749* (0.0334)	0.0750* (0.0331)	0.0727* (0.034)	0.1263* (0.0514)
Auction Price	-0.0088*** (0.0025)	-0.0103*** (0.0028)	-0.0102*** (0.0026)	-0.0086** (0.0029)	-0.0175*** (0.0043)
Dummy for Sub Period 2			-0.0094 (0.0762)		-0.0225 (0.1396)
Mean of trading price				-0.0031 -0.0018	
_cons	0.0802 (0.2639)	0.1508 (0.3028)	0.1559 (0.2984)	0.1912 -0.3093	0.2811 (0.5910)
lnsig2u _cons		-1.0114** -0.3169	-1.0109*** -0.2869	-0.9762*** -0.3306	0.0929 (0.2548)
Statistics					
N	1114	1114	1114		1114
Log likelihood	-592.4348	-572.8482	-572.8431	-570.8979	-572.347
R^2	0.0632	0.0461^	0.0461^	0.0493^	0.0456^
Chi2	41.7655	45.5528	62.4192	62.1237	60.0678
% Correctly predicted	74.78				

Note: Number in brackets represent standard error of the estimate.
^ indicates estimated R^2 = (log likelihood – constant-only log likelihood) / constant-only log likelihood
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level

With regard to penalty design, the summary of estimates in Table 6 show similar results to investment decision model. Subjects tend to be more non-compliant in FPR treatment compared to MGP treatment. Yet, unlike in the investment model, penalty rate provides a highly significant compliance incentive for permit buyers. This finding is in line with *Result 2* in which the compliance rate is higher with higher penalty level in FPR treatment.

MGP treatment generates to highest marginal effect to compliance and this effect is also highly significant. Higher level of make-good factor also increases the likelihood of subject's compliance although this effect is statistically not different to zero. The test statistics of the models validate *Result 3* in which penalty level in MGP treatment yields no differences in compliance rates.

There is an evidence of learning curve over time as the coefficient of *Round* is statistically significant for all random effect models. An opposite effect is observed with variable *Sub Period 2*. In line with the experimental design, the estimates reveal that subjects find it more difficult to be compliant only through permit buying, in particular in Sub Period 2. This effect is undoubtedly true in MGP treatments in which any slight non-compliance by the end of Sub Period 1 can cause a very high pressure on permit demand in Sub Period 2.

It is not surprising that auction price generates a negative effect on compliance incentive because higher permit price increases compliance costs causing the marginal benefit of being non-compliant to increase accordingly. This effect is highly significant although it is much less in magnitude compared to the effect of having MGP treatment. Trading price also has a negative effect on compliance but the effect is only half of that of auction price and it is not statistically significant. It is important to point out that the coefficients on auction price and penalty rate work to countervail each other's effect. Across models we can see that their magnitudes are not much different. In all models except for Model 4, the marginal effect of the penalty rate is smaller than that of the auction price. In Model 4 the inclusion of the mean of trading price moderates the marginal effect of auction price.

The estimates are fairly consistent across models in terms of the sign of the coefficients. Statistically, the random effects binary choice models yield more consistent estimates than the OLS estimator. The OLS model shows that the model has a fairly good predictive power with about 75% of the data correctly predicted. However, the value of R^2 is pretty small and slightly reduced in the random effect models.

5.4. Efficiency

Regression models for efficiency are carried out with Tobit model as the range of possible values are truncated. Interestingly, we find some observations in which the efficiency level is higher than 1 due to low auction price below the optimal equilibrium. Those observations mostly have MGP treatment. The occurrence of that low auction price might be due to over investment which than undermine permit demand. In other cases, low price also happens in sub period 1 in which the financial penalty of non-compliance is zero. Therefore, we only apply a left censoring of zero in the estimation models. Group level data is used to estimate the models as we would like to see the overall efficiency in the market instead of individual optimal behaviour.

The models show pretty similar results across models (Table 7). The first model is performed with cluster robust standard error estimator, with group as the cluster identity. Penalty design treatment variable, price variables, and time variables are used as explanatory variable. Surprisingly, FPR treatment and penalty rate have almost negligible effect on efficiency. As in the previous estimation models, MGP treatment and auction price are highly significant both in economic and statistical terms.

Table 7. Estimates Summary for Efficiency

Regressor for efficiency	Model 1	Model 2	Model 3
	Tobit	Panel data Tobit	Panel data Tobit
Dummy for FPR	-0.0003	-0.0024	0.0094
	-0.0231	-0.0297	-0.0117
Penalty rate	0.0000	0.0001	-0.0004**
	-0.0002	-0.0002	-0.0001
Dummy for MGP	-0.0437**	-0.0395*	-0.0786***
	-0.0156	-0.0184	-0.0127
Dummy for MGP high level	0.0153	0.0154	-0.0058
	-0.0199	-0.0232	-0.0111
Auction Price	-0.0059***	-0.0059***	-0.0055***
	-0.0004	-0.0004	-0.0002
Mean of trading price	-0.0003	-0.0003	-0.0001
	-0.0002	-0.0003	-0.0001
Round	0.0062**	0.0061*	0.0003
	-0.0024	-0.0025	-0.0021
Dummy for Sub Period 2	-0.0697***	-0.0690***	-0.0678***
	-0.0113	-0.0103	-0.0071
Compliance rate			0.5168***
			-0.0373
Investment level			-0.2020***
			-0.0166
_cons	1.1733***	1.1709***	0.9885***
	-0.0324	-0.0313	-0.0324
Sigma _cons	0.0834***		
	-0.0058		
Sigma_u _cons		0.0199*	
		-0.0082	
Sigma_e _cons		0.0810***	
		-0.0056	
N	360	360	360
Log likelihood	383.5838	385.8185	470.3238
Chi2	180.0935	492.9965	1445.322

Note: Number in brackets represent standard error of the estimate.
^ indicates estimated R^2 = (log likelihood – constant only log likelihood)/ constant only log likelihood
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level

Learning effect is also confirmed as the coefficient on R*ound* is highly significant. This indicates that overtime subjects learn to make better decisions in the game which contribute to higher efficiency in the market. The coefficient on Sub Period 2 has a negative sign indicating that the efficiency in this sub period tends to be lower than Sub Period 1. The high financial penalty in the second sub period for MGP treatment might be the underlying reason of this effect. Otherwise, it seems that investing firms attempt to make profit selling in Sub Period 2 by buying more permits at the auction. Nevertheless, this attempt does not seem to be successful as the means of trading price are lower than the auction price 70% of the time, hence the efficiency is also reduced for both buyers who cannot obtain the required permits and sellers who cannot realise their preferred trading price.

Model 2 is very similar to Model 1 except for the fact that the regression is run with panel data Tobit estimator. The estimation results are not much different, but the goodness of fit of the model is increased as shown by the value of the log likelihood.

The inclusion of investment level and compliance rates variables in Model 3 changes the model estimates considerably. The sign on FPR treatment is now positive although it is not statistically significant. Penalty rate, on the other hand, becomes highly significant. This is reasonable as higher penalty rate relates to higher costs in case non-compliance occurs. Similarly, the effect of MGP treatment is almost doubled in this model, while high MGP level is not significant. It can be inferred that with regard to penalty design, MGP penalty type and the level of penalty rate are the main determinants of efficiency.

The important finding from this model is that the investment level and compliance rate has an opposite effect to efficiency. Higher compliance level in the market contributes to higher efficiency. On the contrary, higher investment level will reduce efficiency due to higher investment costs than necessary. As seen from Figure 5, it is also clear that some high MAC firms decide to make investment decision which implies higher total investment costs than optimal in the market. Furthermore, there is a prevailing over-investment in the market which exacerbates that inefficiency.

6. Conclusion

In line with the theory, our results show that different penalty design does not necessarily indicate different permit price. We find that auction prices do not significantly vary across treatments as shown by *Result 1* and the regression models for auction price. The important determinants of auction price are subject's risk attitude and rational thinking ability.

This experiment has shown that contrary to the theory which predicts that there will be no differences in compliance rate as long as penalty level is set above the equilibrium permit price, our results display significantly higher compliance levels in treatments with higher penalty levels for FPR treatment (*Result 2*). This study reveals that subjects learn about different maximum compliance costs related to higher penalty rates, which in turn affects their compliance strategy. However higher penalty rates do not provide different incentive to investment decision.

In MGP treatments, *Result 3* confirms the theory that higher penalty level (make-good ratio) does not produce differences in investment level and compliance rate.

Result 4 points out that when comparison is drawn across different penalty types with the similar penalty level, difference compliance rates are only confirmed for low level penalty treatment. In this case, MGP treatment provides stronger compliance incentive than the FPR treatment although the parameter in the experimental design is slightly lower for make-good ratio (restoration rate of unity) than the penalty rate factor (1.2 of equilibrium price).

The statistics of the estimation models for compliance decision verify *Result 2* and *Result 4* as both the penalty rates and MGP treatment are the significant penalty design variables.

With regard to the Mixed Penalty design, *Result 5* reveals that this double penalty provides higher investment level and compliance rates compared to the baseline low level FPR treatment. Nevertheless, the regression models prove that MGP treatment is the only significant penalty design variable which affects investment decision. The models also verify that subjects behave rationally in making their investment decisions.

A trade-off between efficiency and compliance is revealed as the regression models show that MGP treatment has a statistically and economically significant effect on efficiency. Hence, the penalty design which encourages higher compliance levels might correspond to lower efficiency levels when over-investment occurs in the market. As auction price plays a significant role in investment decision, the presence of risk aversion might in practice indirectly contributes to this over-investment which leads to inefficiency in the market.

Overall, we believe that the experiment has provided valuable insights into how penalty design can influence investment and compliance decisions as well as its subsequent effects on market performance. This insight will help policy makers with regard to how a particular market design might affect other design elements, as well as to provide information regarding the related trade-offs between compliance and over-investment which brings about inefficiency in the market. These trade-offs should be considered before a policy is implemented and laboratory experiment can serve as a test-bed for the policy of interest.

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